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Narrow Band Interference Elimination based on Compressed Sensing in UWB Energy Detector

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ABSTRACT

Wireless communication applications with large signal bandwidth are developed tremendously in recent times. Due to large bandwidth the wide band communication causes huge power consumption and signal deterioration after addition of narrow band interference (NBI). The ultra wide band (UWB) energy detector, which is highly robust against NBI signal is presented. Compressed sensing is implemented to reduce the power consumption at the analog to digital converter with approximated message passing reconstruction. In addition to this, digital notch is employed to eliminate the NBI affected measurements from compressed version of the received signal before applying it to the energy detector. To analyze the efficiency of the detector, the energy detection and bit error probability of the detector in the absence of NBI and after mitigating NBI is compared. The simulation results are the evidence of effectiveness of the presented energy detector.

Keywords: Compressed sensing, narrow band interference, ultra wide band, approximated message passing

1. INTRODUCTION

Digital communication in last decade has resulted in extensive growth of various applications which involved signals of very high bandwidth. Reducing the sampling rate of these signals has become a challenge in many wireless communication applications. Compressive sensing provides reduced and efficient sampling compared to the traditional sampling rate.In the field of short range communication, the impulse-radio (IR) - ultra-wideband (UWB) signals are the most attractive due to their unique properties such as high user capacity, fine time resolution as well as low probability of interception and detection[1,2]. But, the major challenges in employment of IR-UWB is the power consumption in analog to digital converter (ADC) and sensitivity of wide band signals toward narrow band interference (NBI).

According to the Federal Communications Commission (FCC), UWB signals are defined as signals having a fractional bandwidth greater than 20 per cent or signals having an absolute bandwidth greater than 0.5 GHz[3]. There are two techniques to generate a UWB signal. One is carrier based and other is carrier-less. Carrier based technique uses spreading schemes like frequency hopping or direct sequence and makes the architecture complex due to the presence of mixer and other circuitry. The carrier-less technique is also known as IR which uses transmission of short pulses in time domain and occupies the complete frequency band. Its transceiver is simpler than the former technique of UWB signal generation. Also, the transmit power in IR-UWB can be decreased by transmitting the same information over multiple frames, with each frame transmitting at a very low power.

According to Shannon-Nyquist-Whittaker-Kotelnikov sampling theorem[4,5], a band-limited signal $x(t)$ can be recovered fully from its sampled version $x(iT)$ only if $T \leq 1/(2F_{\max})$, where F_{max} is the maximum frequency of the signal. In other words, sampling rate should be equal to or greater than twice the maximum frequency of the signal to reconstruct it completely.But the large bandwidth signals like UWB signals which has 3.1 GHz - 10 GHz band, carry less information, i.e. they are sparse in nature. If those signals are sampled at traditional sampling rate, ADC can be overburdened and it consumes lots of power[6,7], so they need to be sampled depend upon the amount of information contained in the signal. It can be achieved by CS theory proposed by Donoho and Candes[8,9]. According to CS theory, the sparse signal can be recovered properly with lower than the traditional sampling rate. The measurement matrix and reconstruction algorithm play crucial role for efficient performance of CS theory.

CS based UWB energy detector which is highly robust to NBI is presented in this paper. We have implemented the reconstruction based energy detector proposed[10] for analyzing the effect of NBI on UWB signal. To eliminate the NBI effect the digital notch[11] is proposed. After eliminating the NBI affected measurements from UWB signal, energy detection should be similar to the energy detection in the absence of NBI. Major contributions of this article can be summarised as follows:

- Use of the digital notch[11] is proposed, to eliminate the NBI effect added in the UWB energy detector proposed[10].

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- We show that, the performance of CS based energy detector is more effective than the Nyquist rate based detector.
- Also, the energy detection and bit error probability of the detector in the absence of NBI and after mitigating the NBI is analysed.

2. LITERATURE SURVEY

The field of UWB communication employed with CS theory is under tremendous development. The receiver is proposed for IR-UWB communication using CS, which is characterised by bursty traffic and severe power constraints[12]. The receiver can acquire and track the channel response in any of the environmental conditions and severe inter-symbol interference. Proposed receiver[12] is further extended[11] for NBI mitigation using notch out method. The CS theory reconstructs the sparse signal as well as provides the generalised likelihood radio test (GLRT) detector for I-UWB[13]. The GLRT detector is further extended with matching pursuit (MP) algorithm for pilot assisted IR-UWB detection[13,14]. The IR-UWB detector proposed is also further extended to suppress NBI using subspace detection[14,15]. The signal can be theoretically sub-sampled by projection matrix according to CS theory, but the multiplication of matrix and signal needs already sampled received signal. The random matrix is not realizable using hardware and under-sampling is uncontrollable. These problems can be solved by replacing random matrix with analog to information converter (AIC) in CS measuring projection stage[16]. But, this method does not guarantee the precise reconstruction of sampled signal.

Novel differential detection method[17] is proposed which exploits CS framework and optimisation problem is formulated to jointly reconstruct the sparse signal and differentially encoded data. The differential detection method proposed is further extended for multiple symbols using generalised likelihood ratio tests[18]. Methods for channel estimation are provided for CS based UWB communication, time delay estimation is provided[19-21]. There are two types of CS based UWB energy detectors proposed[10]. One is direct compressed energy detection and other is reconstruction based energy detector. In this study, reconstruction based energy detector is employed.

From the above summary, we can say that both the detectors are important with their own merits in different situations. But these energy detectors are very sensitive to the NBI due to large bandwidth symbol. The NBI affected IR-UWB measurements can be mitigated using proposed method[11,15]. The comparison between the proposed methods[11,15] is described in Table 1. From the Table 1, it is evident that notch out approach implemented in this paper is superior to the method presented[15]. The detector employed to mitigate the narrow band interference with the help of notch out method[11]. The detector proposed[15] requires low pulsing rate and perfect timing information as well as discrete cosine transform (DCT) only for energy detection. All the above limitations are overcome by the method presented in this article.

Table 1. Comparisons of NBI mitigation methods

Features	Oka[11], *et al.*	Wang[15], *et al.*
Pulsing rate	Independent	Low
Timing issue	Robust	Requires perfect timing
Discrete cosine transform	Do not require	Requires
Domain of CS ensembles	Fourier	Time

3. COMPRESSED SENSING

To convert the analog signal into digital with the traditional method, first step is to sample it and then compress by eliminating zero or near to zero valued samples. In this process, large power consumption is required for sampling the complete signal. But he compressed sensing unifies both, the compression and sampling processes so it is called as compressive sampling[8,9]. Compressed sensing is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to under determined linear systems.

As shown in Fig. 1, in the process of CS, measurement matrix and reconstruction algorithm play important role in compressing and reconstructing the signal respectively. The linear system to be passed through the CS process can be considered as,

$$Y = \Phi X \tag{1}$$

where X is an $N \times 1$ vector of optimisation variables, Φ is an $M \times N$ dimensional measurement matrix and Y is an $M \times 1$ vector of compressed measurements as $M < N$. Here, X is a sparse vector that contains less number of non-zero valued samples than the zero valued samples.

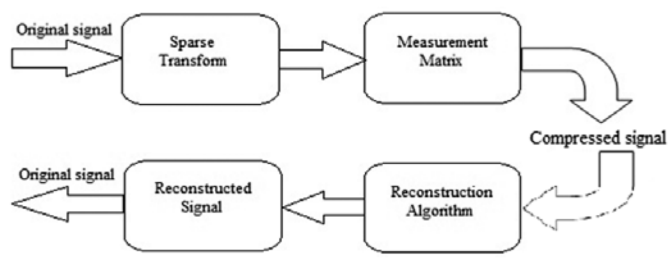

Figure 1. Process of compressed sensing theory.

The measurement matrix converts the signal as $\mathbb{R}^N \rightarrow \mathbb{R}^M$. But measurement matrix should satisfy restricted isometry property (RIP) to provide recoverable compressed version of the original signal[9]. For each integer $= 1, 2, \cdots$, RIP property define the isometry constant δ_s of a matrix Φ as the smallest number such that

$$(1-\delta_s)X_{l2}^2 \le \Phi X_{l2}^2 \le (1+\delta_s)X_{l2}^2 \tag{2}$$

holds for all s-sparse vectors[9] X. A vector is said to be s-sparse if it has at most s non-zero entries. This property is satisfied by the random matrices like Gaussian, Bernoulli and also structured matrix like Fourier[10].

The challenging task in CS theory is to recover the original signal from incomplete samples. For reconstruction process[3], X represents the unknown vector and the problem is to find X from Y given Φ. This problem is popularly written with l_2-norm as,

$$P_2 : \arg \min_X \|X\|_2^2 \text{ such that } Y = \Phi X \tag{3}$$

The minimum norm solution can be obtained from l_2 -norm but, it measures total energy of the vector X rather than handling individual element. It cannot reconstruct the original signal properly from compressed version. The number of nonzero elements from X can be counted by replacing squared l_2-norm with an l_0-norm[3] as,

$$P_0 : \arg \min_X \|X\|_0 \text{ such that } Y = \Phi X \tag{4}$$

The l_0-norm solution provides sparse solution but not unique, unlike l_2-norm solution. But, the l_1-norm solution provides compromise between l_1-norm and l_2-norm solution. It is closer to l_0-norm in terms of sparsity whereas it is closer to l_2-norm in terms of uniqueness or being convex. It can be written as,

$$P_1 : \arg \min_X \|X\|_1^1 \text{ such that } Y = \Phi X \tag{5}$$

P_1 is a convex optimisation problem and can be easily solved by a linear programming (LP). P_1 is also known as basis pursuit (BP)[22].

The compressed signal can be recovered exactly under two conditions (1) original signal should be sparse (2) the measurement matrix should satisfy RIP property. There are mainly three types of reconstruction algorithms[23] as shown in Fig. 2.

First is the greedy pursuit, such as the orthogonal matching pursuit (OMP) method[24], the stagewise OMP (StOMP) method[25] and the regularised OMP (ROMP) method[26], the compressive sampling matching pursuit (CoSaMP) method[23], where these methods build up an approximation one step at a time. Second is the convex relaxation algorithm, such as the interior-point method[27], the gradient projection method[28] and the iterative thresholding algorithm[29] and the last is the combinatorial algorithms that acquire structuredsamples of the signal that support rapid reconstruction by group testing[23]. Each algorithm has its own pros and cons in a particular reconstruction problem. So the reconstruction algorithm should be chosen according to the requirement in specific application.

4. SYSTEM MODEL

The system described in Fig. 3 transmits the j^{th} information symbol with $m-$ary pulse position modulation (PPM). In PPM, the delay is added in the signal for modulation which is easy in implementing. To transmit the j^{th} information symbol, consider a signal $U_j(t)$ containing N_F frames of length T_F, so that the signal length becomes $T = N_F \times T_F$ and delayed by $T_m = \frac{T_F}{m}$ for PPM modulation. The transmitted j^{th} symbol can be represented as $U_j(t) = \sum_{i=0}^{N_F-1} b\big(t-(i+jN_F)T_F - c_j T_m\big)$, where $c_j \in (0,1,\cdots,m-1)$ and $b(t)$ is second derivative of Gaussian pulse with unit energy of duration $T_b \ll T_m$. If $h(t)$ is represented as impulse response of Gaussian communication channel, then the received signal is,

$$r(t) = U_j(t) * h(t) + w_j(t) + I_j(t) \tag{6}$$

where $w_j(t)$ and $I_j(t)$ is the additive noise and interference symbol of bandwidth I_B, corresponding to j^{th} information symbol respectively and $U_j(t) * h(t) = g_j(t)$ is the received pulse waveform of bandwidth U_B with duration T_g.

For Nyquist-rate sampling of the symbol, we take N samples per frameperiod T_F, whereas N/m samples for each slot. Then the i^{th} sampled frame corresponding to j^{th} symbol is given by,

$$r_{j,k}^i = r\left(iT_F + \frac{kT_F}{N}\right) = g_{j,k}^i + w_{j,k}^i + I_{j,k}^i \tag{7}$$

for $k = 0,1,\cdots,N-1$. We assume that the NBI zero mean, unit power elements whereas, $w_{j,k}^i$ has independent identically distributed (i.i.d.) zero mean Gaussianwith variance σ^2. The sampling of received signal using Nyquist-rate consumes large amount of energy due to sparse nature of the signal. The zero or near to zero valued samples produced after applying Eqn. (7) are eliminated. This wastage of energy can be removed by replacing Nyquist sampling with compressed sampling.

For compressing the signal, measurement matrix Φ is so chosen that it contains rows which are approximately orthogonal to each other[10]. Now, the received signal is applied to $M \times N$ matrix Φ to get compressed version of signal. For i^{th} frame, applying CS to Eqn. (6), we get,

$$D_j^i = \text{Ö} r_j^i = G_j^i + V_j^i + Z_j^i \tag{8}$$

where D_j^i is the $M \times 1$ compressed measurement vector.

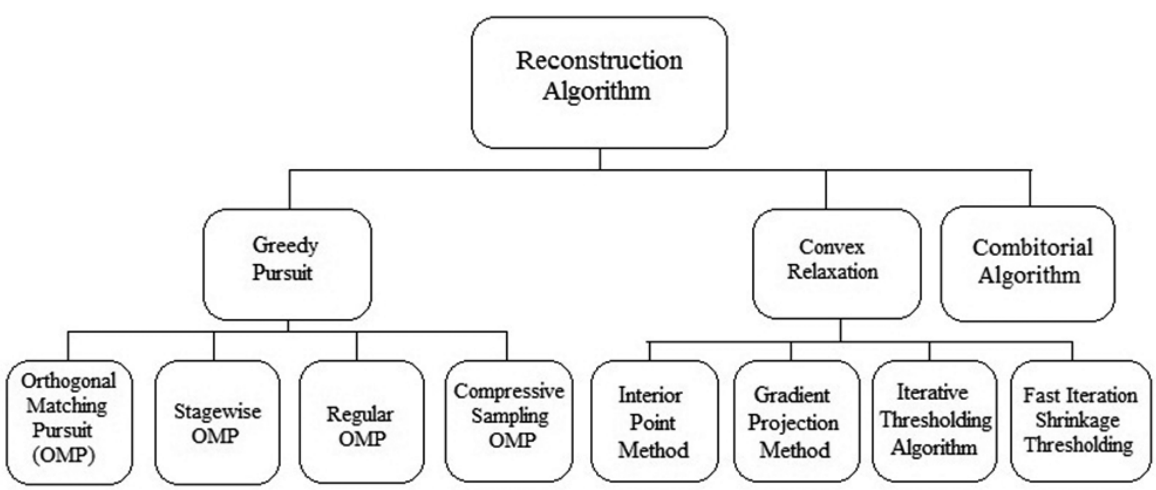

Figure 2. Classifications of reconstruction algorithms in CS theory.

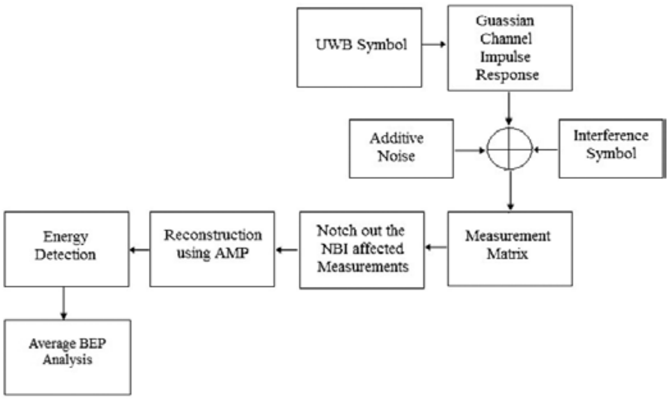

Figure 3. Block diagram of NBI robust UWB energy detector.

Similarly V_j^i and Z_j^i are the compressed versions of noise and NBI symbol respectively. Along with huge advantages, the UWB symbol has sensitivity towards NBI due to its wide bandwidth feature. The UWB measurements are deteriorated due to addition of NBI symbol and UWB symbol.

The 'notch out' method[11] to suppress the NBI affected measurements from compressed vector is applied. In this method, first step is to choose Fourier ensemble of magnitude $1/\sqrt{N}$ and its frequency is selected from $\left(F_c-\frac{\Omega}{2},F_c+\frac{\Omega}{2}\right)$, which are decoherent with UWB signal and coherent with NBI, to ensure that only few measurements are affected by NBI. Then, we implement notch to mitigate NBI affected measurements. For at most 1 NBI we find,

$$s = \underset{s\in\{0,1,\cdots,M-1\}}{\operatorname{argmax}} \left|D_s\right| \tag{9}$$

Now, take $A \sim \alpha\frac{I_B}{\gamma}$, where $\gamma = \frac{U_B}{M}$ is test function spacing and α is the safety factor lies between 4 to 8. The NBI mitigated measurements can be obtained by notching out $A+1$ measurements around the index s. If $N_I > 1NBI$ is expected in the signal then this notching procedure is performed for N_I largest values from compressed measurement vector D. To reduce the time required for reconstructing the frames individually, the NBI eliminated measurements of N_F frames are averaged and applied to approximated massage passing (AMP) algorithm to reconstruct the original signal[10]. The iterative thresholding (ITH) algorithm has better simplicity and speed than other reconstruction algorithms, but its performance is not good in sparsity-undersampling (SU). However, the AMP performs well in SU along with better speed and simplicity. The AMP can be explained briefly for n^{th} iteration as follows,

$$y_j^{[n+1]} = S\left(y_j^{[n]} + \Phi^T x_j^{[n]}, \tau^{[n]}\right) \tag{10}$$

where

$$x_j^{[n]} = D_j - \Phi y_j^{[n]} + \frac{1}{\mu} x_j^{[n-1]} \left\langle S'\left(y_j^{[n-1]} + \Phi^T x_j^{[n-1]}, \tau^{[n-1]}\right)\right\rangle \tag{11}$$

Here τ is iteratively updating threshold and $\left\langle S'(\bullet)\right\rangle$ is the average of derivative all samples of soft-thresholding over N samples. The value provided by y_j^n is the reconstructed vector of signal. Now, these samples are provided to reconstruction based energy detector, which is provided[10]. For N_m non-zero samples, detection is done as follows,

$$\hat{c}_j^{(R-ED)} = \max_{c_j} \sum_{p=0}^{N_m-1}\left[\frac{1}{N_F}\sum_{i=0}^{N_F-1}\left[\check{b}_k\right]_{iN+c_kN_m+p}\right]^2 \tag{12}$$

The Nyquist rate energy detection is obtained by replacing reconstructed samples with Nyquist rate samples[12]. For analysis of energy detection, the bit error probability (BEP) of both Nyquist-rate energy detector and reconstruction based energy detector is given in same[10].

$$P^{(R-BEP)} = 1-\frac{2\tilde{A}\left(\frac{N}{2}\right)}{\frac{N}{2}\left[\tilde{A}\left(\frac{N}{4}\right)\right]^2}\left[\frac{\sigma_r\sigma_w}{\sigma_r^2+\sigma_w^2}\right]^{\frac{N}{2}} \times 2F_1\left(1,\frac{N}{2};\frac{N}{4}+1;\frac{\sigma_r^2}{\sigma_r^2+\sigma_w^2}\right) \tag{13}$$

where $2F_1(\cdot,\cdot;\cdot;\cdot)$ is the Gaussian hyper geometric function.

$$P^{N-BEP} = 1-\frac{2\tilde{A}\left(\frac{N}{2}\right)}{\frac{N}{2}\left[\tilde{A}\left(\frac{N}{4}\right)\right]^2}\left[\frac{\sigma_{\beta 0}\sigma_{F0}}{\sigma_{\beta 0}^2+\sigma_{F0}^2}\right]^{\frac{N}{2}} \times 2F_1\left(1,\frac{N}{2};\frac{N}{4}+1;\frac{\sigma_{\beta 0}^2}{\sigma_{\beta 0}^2+\sigma_{F0}^2}\right) \tag{14}$$

where $\sigma_{\beta 0}^2 \triangleq \left(1+\frac{\sigma^2}{N_F}\right)$ and $\sigma_{F0}^2 \triangleq \left(\frac{\sigma^2}{N_F}\right)$.

5. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the simulation results using the detector developed in previous section. We consider, the UWB signal is transmitted along Gaussian distributed physical channel with the elements having zero mean and unit variance. The received signal is compressed by applying it to the random measurement matrix. Let the number of interference, $N_I = 1$ for experiment purpose. But, we can simulate this detector for multiple numbers of interferences. In AMP algorithm, the threshold policy is in the form of $\tau^{[n]} = \delta\sigma_w^{[n]}$, which is infeasible in practice. So, threshold can be updated as suggested in[9],

$$\tau^{[n]} = \tau + \frac{1}{\mu}\tau^{[n-1]}\left\langle S'\left(x_k^{[n-1]} + \Phi^T y_k^{[n-1]}, \tau^{[n-1]}\right)\right\rangle \tag{15}$$

where τ is a constant.

For analysis purpose, we have considered four detectors. The first detector is based on Nyquist rate sampling, the second is based on compressive sampling i.e. reconstruction based, the third detector is having NBI effect and in forth detector the NBI mitigation method is implemented. All the four detectors are compared with each other with respect to signal to noise ratio (SNR in dB) in Figs. 4 - 7 and with respect to compression ratio (mu) in Figs. 8 - 11. All the detectors have same transmission parameters. The transmitted second derivative of Gaussian pulse has duration of 1 ns. For experimentation purpose, we take frame length as 100 ns and number of frames in one symbol is 30, so the duration of symbol is multiplication of N_F and T_F. For every frame, the number of samples is considered to be 200.

All the detectors are analysed with Eqns. (12) and (13) for energy detection and bit error probability respectively. Due to implementation of orthogonal random matrix at compression, the plot of ABEP is following the plot of ED in all the simulated results.

From Fig. 4 and Fig. 8 we can observe that, there is large difference between energy detection of Nyquist rate based and compressive sampling based energy detectors. The CS based energy detectors gives better energy detection than the traditional sampling based energy detectors. After adding the NBI symbol with UWB symbol, the effect of interference can be observed in Fig. 5 and Fig. 9. The NBI affects the UWB signal energy severly.

Then the notch out method is implemented to eleminate the NBI affected measurements from compressed measurements. After eliminating the NBI effect, it is compared with the detector having NBI effect in Fig. 6 and Fig. 10. The comparison shows that the energy detection after employing digital notch is improved. The Fig. 7 and Fig. 11 shows that the energy detection before adding NBI is similar to the energy detection after mitigating NBI. It presents the efficiency of

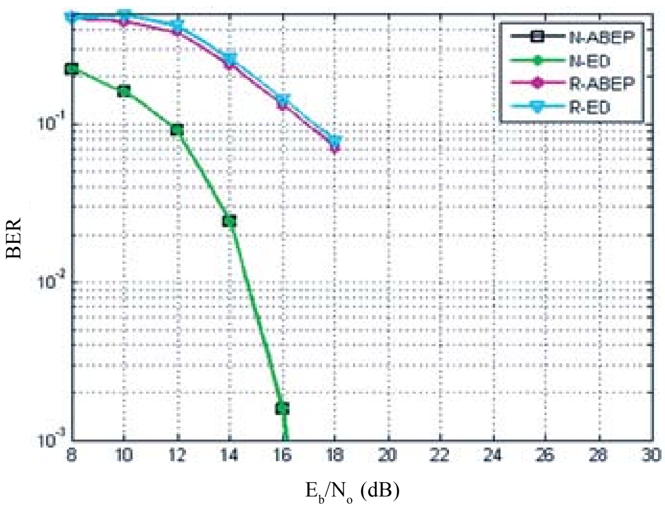

Figure 4. Comparison of Nyquist Rate and reconstruction based energy detectors w.r.t. E_b/N_o.

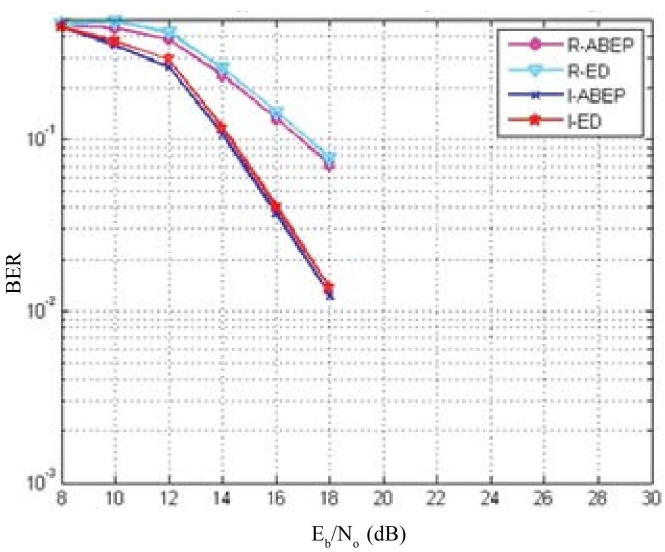

Figure 5. Effect of NBI on reconstruction based energy detector w.r.t. E_b/N_o.

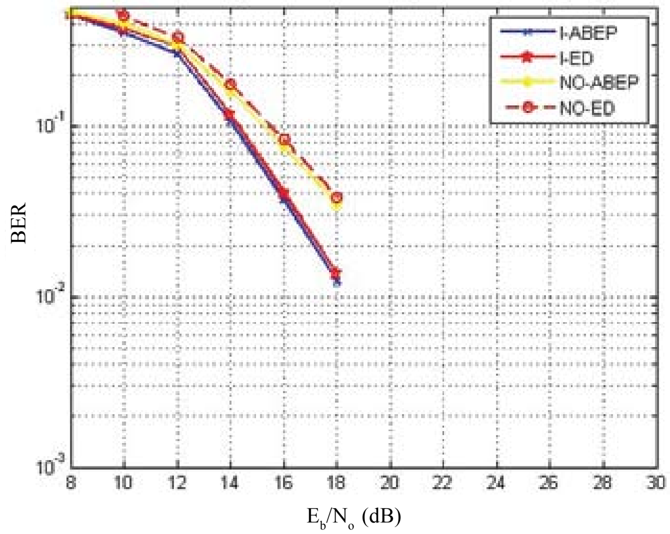

Figure 6. Comparison of detectors in the presence of NBI and after mitigating NBI w.r.t. E_b/N_o.

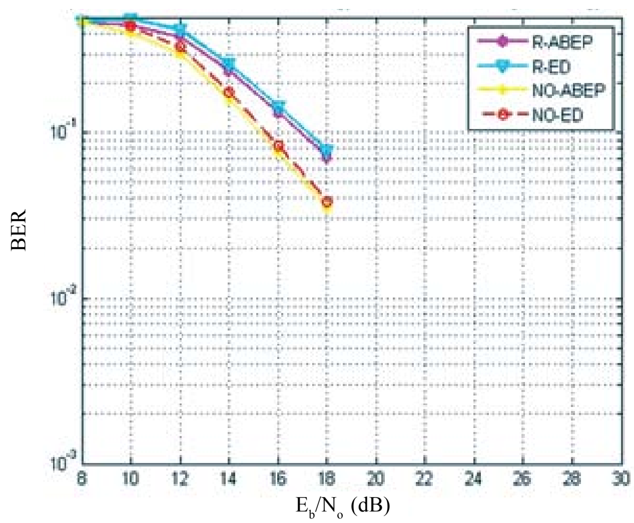

Figure 7. Comparison of detectors in the abcence of NBI and after notching out NBI w.r.t. E_b/N_o.

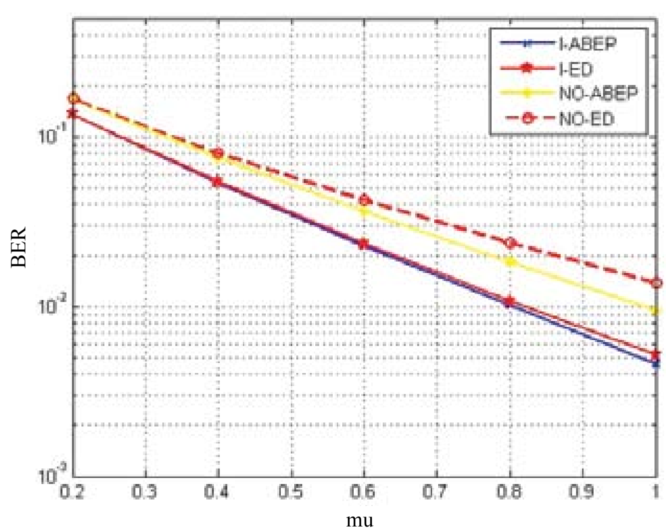

Figure 8. Comparison of Nyquist rate energy detector and compressed sampling based energy detector w.r.t. mu.

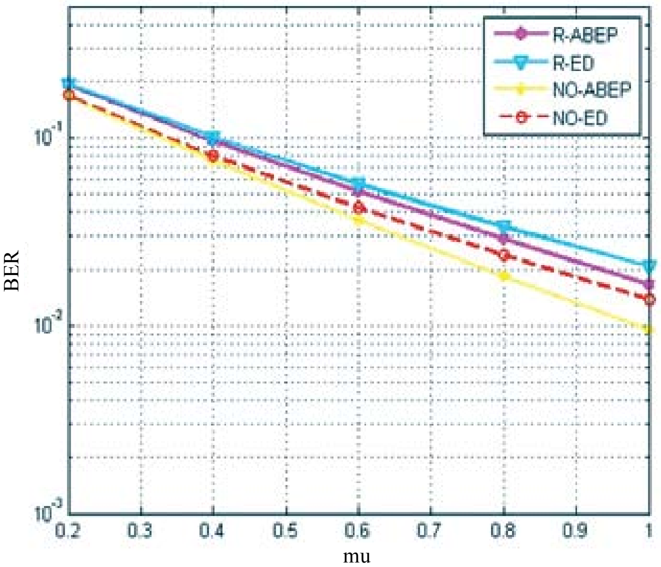

Figure 9. Comparison of energy detector in the absence of and in the presence of NBI w.r.t. mu.

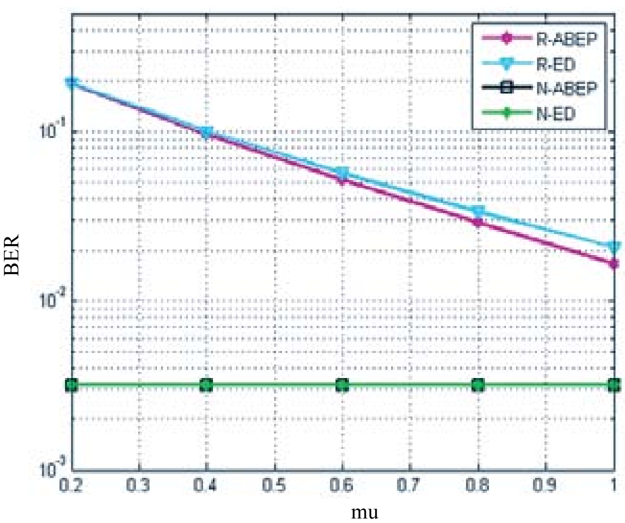

Figure 10. Comparison of energy detector in the presence of NBI and after mitigating NBI.

the notch out method to remove the NBI from the compressed version of the signal. It is the evident that the notch out method removes the NBI successfully.

6. CONCLUSIONS

In this study, authors presented the CS based UWB energy detector which mitigate the NBI affected measurements. We have analysed the performance of the presented energy detector by using theoretical expression of energy detection and bit error probability with respect to signal to noise ratio (SNR) as well as compression factor (μ). The experimental results show that the presented system performs efficiently in the presence of NBI. Also it has been shown that, the reconstruction based energy detector performs better compared to the Nyquist rate based energy detector. The presented system can be further implemented with hardware by using analog to information (AIC) and CS.

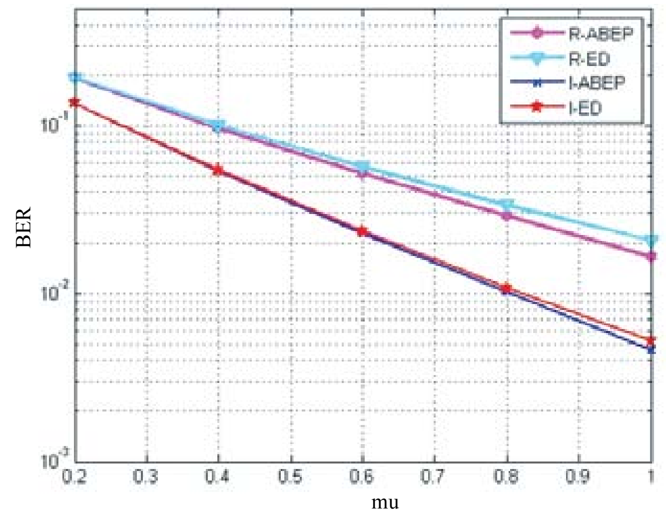

Figure 11. Comparison of energy detector in the absence of NBI and after mitigating NBI w.r.t mu.

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